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Understanding human-centred artificial intelligence in the banking sector

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Abstract The advent of smart digital devices and social media has shaped how consumers interact and transact with their financial institutions. Consumers increasingly want hyper-personalised interactions that are more frequent and proactive, while financial institutions have a growing need to cater to consumers' new demands. Financial institutions, such as banks, continuously adapt to the latest technologies to keep pace with evolving customer behaviours, needs, and experiences. One such emerging technology is artificial intelligence (AI). Many organisations realise the potential of AI; however, a human-centred AI system must be capable of understanding human characteristics and making decisions like humans. This paper presents an empirical study, involving survey participants from three different groups: banks, IT vendors and focus groups. Emphasis is placed on understanding the effect of practising a co-development mindset between these three key stakeholder groups on the outcome of developed human-centred AI-enabled products and services. The survey results show that capturing and processing human emotions (HE) to train an AI model improves customer experience and trustworthiness, and a co-development mindset practised between the IT vendor and the bank will positively influence the effectiveness of human-centred AI-enabled products and services.

KEYWORDS: AI principles, human-centred AI, AI transparency, customer experience, banking

INTRODUCTION

Banking and financial sectors are still in the infancy of implementing artificial intelligence (AI) and its associated technologies.
As a result, the adoption of such niche technologies not only requires a large amount of time, effort and money, but also requires greater caution in managing and mitigating its associated risks in terms of technology and governance, especially when implementing in highly sensitive industries such as banking and finance. Furthermore, financial technology (FinTech) and technology giants entering the banking business puts banks under increasing pressure to adopt AI technologies to stay competitive. For traditional banks to transform completely into digital banking, they must develop products and services to meet customer needs more personally and intuitively with a human touch.

AI with a human touch, or human-centred AI (HCAI), is a discipline that aims to ensure that AI meets customer needs in a transparent and efficient way. A continuous machine learning (ML) process that closely interacts with humans must be given inputs so that it can understand human elements such as communications, ethics, emotions and behaviour.[1] To leverage the power of AI, banks must ensure that AI/ML models are capable of processing human emotions (HE) and understanding human thinking. In addition, AI/ML models must apply AI principles with transparency, ie they must make automated decisions ethically and be able to deal with intended and unintended consequences. Research has been conducted on implementing HCAI products and processes in the banking sector[2] as a means to improve customer experience. The aim of the research study was to answer the following research questions.

- What causes the banking sector to increase its use of AI?;
- Why is AI transparency necessary when developing effective HCAI products?;
- Why must banks practise a co-development mindset, working with IT vendors and focus groups, when designing and developing HCAI products?

THEORITICAL MODEL

To develop effective HCAI products, complex data must be captured from various omni channels and other trusted sources. Training AI models with such complex data must satisfy AI principles and AI characteristics with more transparency in order to gain a higher level of acceptance and trust over the decision taken by the model. To develop such a trusted system, a strong co-development mindset must be practised between banks, IT vendors and focus group companies. Figure 1 shows the theoretical model consisting of four independent variables (‘HE’, ‘human minds’, ‘AI transparency’ and ‘co-development mindset’), one dependent variable (‘effective AI-enabled products’ [EAPS]) and one outcome variable (‘customer experience’).

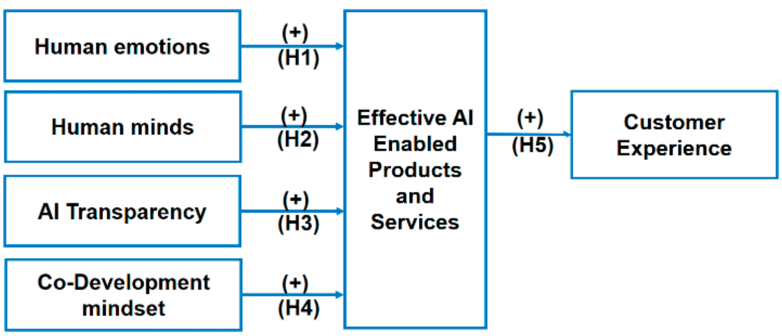

Figure 1: Theoretical model to enhance customer experience through HCAI

The following sections discuss five hypotheses that were developed for the five constructs.

Hypothesis 1

H1: The degree of processing HE positively influences the effectiveness of human-centred AI-enabled products and services.

There is an importance of interpreting domain-specific HE in association with correct decision making and rational thinking similar to humans. Processing HE helps HCAI systems understand the rationale behind HE emotions in-depth. Therefore, to develop a completely automated decision-making system with a human touch, various HE, such as facial expressions, gestures, voice modulation, captured in various formats must be integrated as part of training the ML models. Thus, processing HE will positively influence the effectiveness of HCAI products with a human touch. Hence, the independent variable 'HE' is the first primary construct used in the proposed model.

Hypothesis 2

H2: The degree of understanding the human mind positively influences the effectiveness of human-centred AI-enabled products and services.

Human minds (understanding customer thinking) is another critical factor required for ML models to predict and make autonomous decisions similar to humans. In the field of psychology, 'theory of mind' is an essential intellectual ability that broadly covers the potential to correctly interpret and understand people's states such as their feelings, passions and knowledge, and the capacity to understand these may vary among individuals.[3] Capturing human minds will positively influence HCAI products. Hence, the independent variable 'human minds' is the second primary construct used in the proposed model.

Hypothesis 3

H3: The degree of increase in AI transparency positively influences the effectiveness of human-centred AI-enable products and services.

ML models must be transparent when processing 'HE' and 'human minds'. The rationale behind the algorithms used by the models is critical in gaining trustworthiness over HCAI products. A high level of transparency helps to mitigate the risks associated with ethics, bias, consequences, accountability, explainability and interpretability. Processing the customer's emotions and capturing the customer's mindset with more transparency will positively influence the HCAI product's effectiveness. Hence, the independent variable 'AI transparency' is the third critical construct used in the proposed model.

Hypothesis 4

H4: The co-development mindset between the IT vendor and the bank will positively influence the effectiveness of human-centred AI-enabled products and services.

Practising a co-development mindset helps in the design and development of innovative technologies by bringing technology and people closer.[4] Self-service banking channels are being introduced to provide improved services with a human touch today as the industry moves towards automation. A human independent facility will not be possible unless both banks and their technology vendors believe that knowledge spill over will mutually benefit both parties by revealing their core competencies selectively. To gain a 360-degree customer perspective, focus group companies need to be involved at every critical stage of the development of HCAI products. Practising a co-development mindset is another key factor of product effectiveness. Therefore, 'co-development mindset' is added to the proposed model as a fourth construct.

Hypothesis 5

H5: The effectiveness of human-centred AI enabled products and services has a positive impact on the customer's experience.

'Customer experience is defined as the sum of all experiences that a customer has at every touchpoint of the customer-company relationship.'[5] In the digital age, customers are switching more often to different digital channels and service providers. It is a challenge for traditional banks to come up with products that complement their existing services in order to retain and improve the experience of their customers. Developing more innovative products, considering all four independent constructs, helps to develop HCAI products that improve customer experience, which in turn helps to retain existing customers and opens up avenues to new business opportunities. Thus, EAPS is introduced as the dependent variable in the model.

METHODOLOGY

To our knowledge, no prior empirical study exists that covers the collaboration between banks, IT vendors and focus group companies in the development of customer-centred AI-enabled banking products. For this paper, we used an explanatory study method to establish the relationships between the constructs ('HE', 'human minds', 'AI transparency', 'co-development mindset' and 'customer experience').[6] The study aims to examine whether predictor variables have any positive influence on the outcome variable, as well as to determine the importance of capturing customer emotions and minds through AI. We used Statistical Package for the Social Sciences (SPSS) software to analyse our survey results.

Survey design

We used an anonymous online survey questionnaire with a set of close-ended questions and an open-ended question for each construct. Inputs for the close-ended questions were captured using a Likert scale in the range of 1 to 6. The open-ended question for each construct aimed to get the participants' insights and other related information.[7] The views and perspectives gathered from the open-ended questions provided insights into stakeholders' collaboration strategy, technology adoption, competencies and importance of considering human capabilities when developing HCAI products.

Survey participants were categorised as shown in Table 1. As banks are not technology companies, they strategically outsource their IT activities to several third-party IT vendors.[8] The optimal vendor outsourcing strategy will depend upon various attributes, such as the bank's size, core business type (retail banking, corporate banking, investment banking, private banking, etc.) and technology investment capacity.

Table 1: Targeted participants and IT company categories surveyed

Comany category	Description
Banking software	Banking software companies that develop banking solutions, used by banks to run their business operations as well as support digital transformation.[9]
FinTech	Financial technology companies specialising in developing AI technologies for banks.
Focus group	Companies specialising in interacting with people in a specific market segment for a guided discussion about business ideas.

The survey was conducted among three different types of organisations, as shown in Table 1. First, the survey was carried out with various senior management individuals such as chief executive officers (CEOs), chief technology officers (CTOs), chief information officers (CIOs) and senior vice presidents (SVPs) from 39 software organisations, including the top-ranking core banking software companies specialising in developing banking solutions. Secondly, the survey was conducted with senior executives such as founders, CIOs and CTOs from 31 FinTech organisations specialising in developing AI-based products and solutions for the banking industry. Lastly, the survey was carried out with 36 participants from 20 market research organisations offering focus group discussion services across several verticals, including software companies that provide banking solutions.

The survey questions were grouped under the following categories under each company category:

- Understanding HE;
- Understanding human minds;
- Developing AI products and services with co-development mindset;
- AI operations;
- EAPS and services;
- Customer experience.

The survey questionnaire was designed to capture the participants' responses based on Likert items, forced choice on a scale of 1 to 6 as follows:

- Strongly disagree;
- Disagree;
- Disagree to some extent;
- Agree to some extent;
- Agree;
- Strongly agree.

The same survey questionnaires were shared with participants from banking software companies and FinTech companies whose core capabilities and focus are technology-centric. For the focus group companies, a separate questionnaire was designed and distributed, as the companies' core capabilities and focus was people-centric.

Measuring reliability

The reliability of the survey questionnaire was measured by the degree of correlation among questionnaire items and the degree of consistency in the measurement of the intended construct using Cronbach's alpha coefficients, which is commonly used to measure reliability. Cronbach's alpha value between 0 and 1 is considered positive, and the reliability strength is determined by how close the alpha is to 1. The reliability value ranges from $\alpha < 0.5$ (low reliability), $0.5 > \alpha < 0.70$ (moderate reliability), $0.70 > \alpha < 0.90$ (high reliability) and $\alpha > 0.90$ (excellent reliability).[10] The main purpose of testing the reliability is to check whether the research instrument consistently provides the same results.

Population categorisation

In the overall process of data collection, identifying the right participants and gaining their consent to take part in the survey was the biggest challenge and the most time-consuming task since it requires internal approval processes due to their organisational policies, especially in the cases of industries that operate in sensitive domains (eg banking). To overcome such challenges, the participating companies were categorised (Cat 1, Cat 2 … Cat n) based on the organisation type (Org 1, Org 2 … Org n). Figure 2 shows the vendor company categorisation approach followed for this study.

For example, vendor organisations such as Accenture, Temenos, Tata Consultancy Services, etc., were categorised under core banking software companies. Similarly,

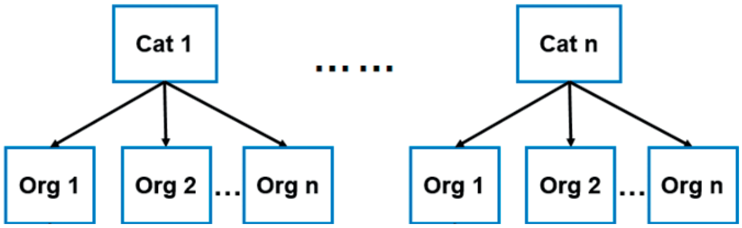

Figure 2: Categorisation of vendor companies

organisations like H20.ai, Finbots.ai, Kore.ai, etc., were categorised under FinTech and start-ups. In addition, organisations such as Qualtrics, Deloitte, Ipsos, Kantar, etc., were categorised under the focus group companies.

Data collection approach

Although vendor companies provide similar services to their banking clients, they may be influenced by organisational climate, culture, leadership and other factors. Therefore, to capture high-quality data, gain a deeper understanding of the study and avoid data bias, a single participant's opinion was collected from each firm ('one-from-many') rather than capturing many participants' views from each organisation ('many-from-one'), as shown in Figure 3.

Data repository

A formal invite was sent to the participant's business e-mail to get their consent to participate in the online survey, and upon receiving the participant's consent the anonymous online survey link was shared to the participant's business e-mail. Each participant's survey data was captured in a separate database that was created for each company category (banking software companies, FinTechs, focus groups), as shown in Figure 4. This approach enabled the survey data to be analysed separately, considering different perspectives of the participant's domain expertise.

Testing

Before applying any statistical method to analyse the data, a reliability test was performed on the survey questions under

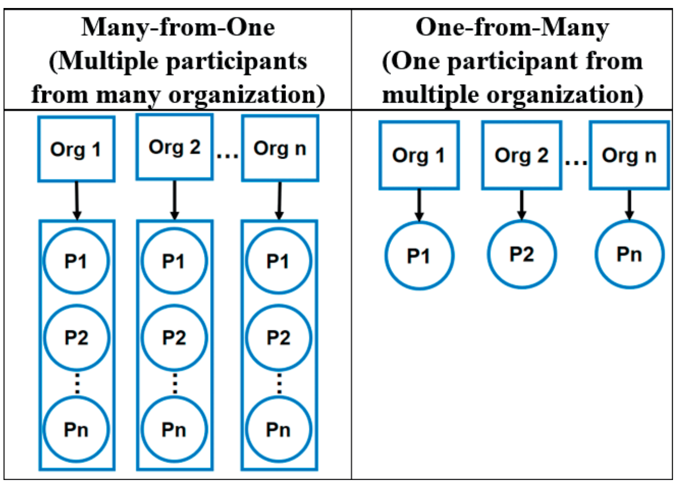

Figure 3: Participants' involvement from different organisation

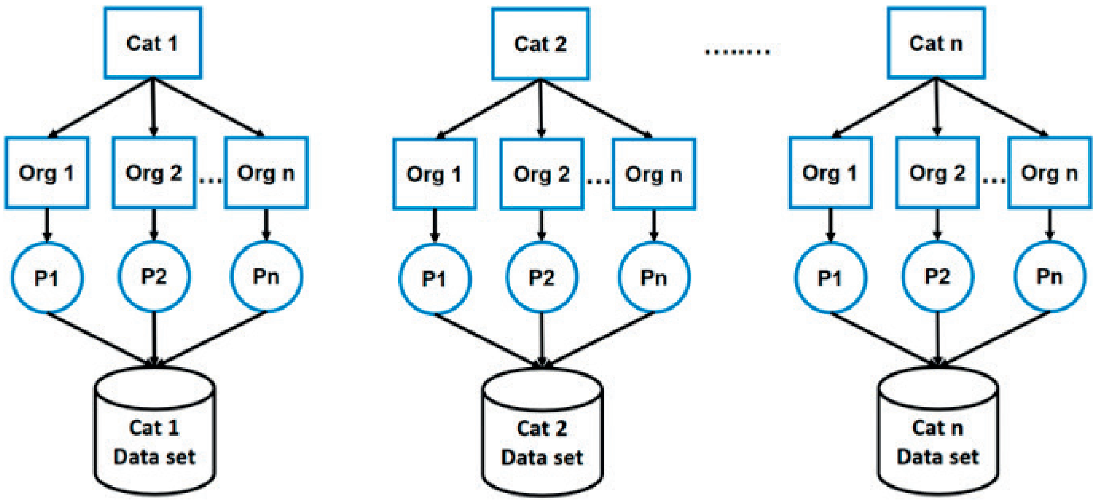

Figure 4: Data collection model

each model construct. Then, statistical methods, such as linear regression and regression analysis, were applied to the survey data collected. These methods were used to see if statistically significant relationships existed between the independent variables and the outcome variables, as shown in Table 2. A hypothesis was accepted or rejected based on the degree of influence between independent and dependent variables.

RESULT AND ANALYSIS

A set of survey questions was created and grouped for each model construct. After completing the data collection stage, the proposed theoretical model hypotheses were tested for each survey dataset. Finally, the survey data was analysed, as shown in Figure 5.

Statistical model

The relationship between the dependent and independent variables was determined through linear regression models. For example, if Y is a dependent variable and X is an independent variable, as shown in Table 3, a linear regression model can be used to determine the relationship between Y and X.

The goodness of fit of a linear regression model is measured using a statistical measure called R-square. R-square ranges from 0

Table 2: Statistical model to infer relationship between variables

Model	Independent Variable	Dependent Variable
Liner regression	• Human emotions • Understanding human minds • AI Transparency • Co-development mindset • Effective AI-enabled products and services	• Effective AI-enabled products and services • Customer experience
Analysis of variance (ANOVA)	• Human emotions • Understanding human minds • AI Transparency • Co-development mindset • Effective AI-enabled products and services	• Effective AI-enabled products and services • Customer experience

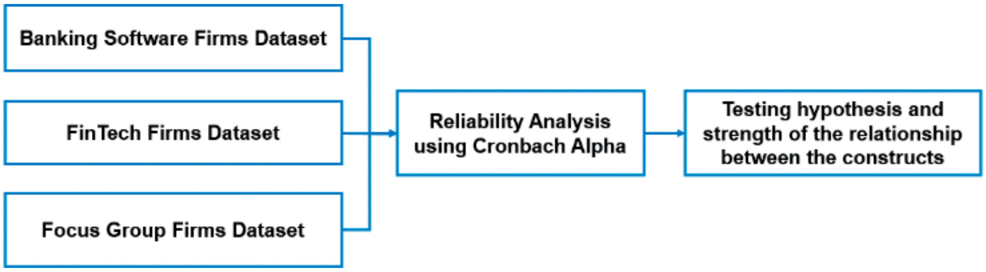

Figure 5: Data analysis process flow

Table 3: Linear regression model

Y	Dependent variable	$Y = A + B * X + e$
A	Intercept	
B	Coefficient of the independent variable X	
X	Independent variable	
e	Error component	

to 1, and if the R-square value is high, the model is a good fit; however, the model is not a good fit if the R-square value is low. The R-square is measured using the formula shown in Table 4.

If the coefficient is positive, it indicates that if the independent variable increases, it will have some positive effect on the dependent variable, ie if the independent variable increases, the dependent variable also increases. Next, the p-value of the coefficient is to be checked. It can be concluded that a coefficient is significant if its p-value is less than 0.05. On the other hand, if the p-value is more than 0.05, it is considered insignificant.

Reliability analysis using Cronbach's alpha

A reliability test was conducted on each construct's survey questions. Reliability is the determination that the research instrument consistently provides the same results.[11] The survey questionnaire was designed to capture the participant's responses based on Likert items on a scale of 1 to 6. Cronbach's alpha value between 0 and 1 is considered positive, and the reliability strength is determined by how close the alpha is to 1. Cronbach's alpha is measured using the formula shown in Table 5.

The reliability value ranges from alpha < 0.5 (low reliability), 0.5 > alpha < 0.70

Table 4: Measuring R-square

yi	i[th] dependent observation	R-Square = $1 - \frac{\sum_1^n (y_i - \bar{\hat{y}})^2}{\sum_1^n (y_i - \bar{y}_i)^2}$
$\bar{y}$	Mean of the dependent variable.	
$\hat{y}$	predicted value of the i[th] dependent observation based on the linear regression model = A + B*Xi	

Table 5: Cronbach's alpha formula

ρ_T	tau-equivalent reliability	$\rho_T = \frac{k^2 \overline{\sigma_{ij}}}{\sigma_X^2}$
k	number of items	
σ_{ij}	covariance between Xi and Xj	
σ_X^2	item variances and inter-item covariance	

(moderate reliability), 0.70 > alpha < 0.90 (high reliability), and alpha > 0.90 (excellent reliability).

Reliability analysis of banking software dataset

The survey included 39 potential participants from 39 banking software companies. The results of the reliability analysis are shown in Table 6. Cronbach's alpha for all measures were above the moderately reliable range.

The consolidated statistical results and the strength of the direct association between the dependent and independent variables of all five hypotheses applied to the banking software companies' dataset are shown in Table 7.

Reliability analysis of FinTech dataset

In total, 31 unique potential participants took part in the survey from 31 fintech companies. The results of the reliability analysis are shown in Table 8. Cronbach's

Table 6: Results of reliability analysis (software companies' dataset)

Measure	Abbreviation	No of items	Cronbach's Alpha
Effective AI products and services	EAPS	6	0.720
Human emotions	HE	5	0.803
Human minds	HM	5	0.748
Co-development mindset	AIT	8	0.805
AI-transparency	CDM	8	0.834
Customer experience	CE	4	0.655

Table 7: Strength of relationship between constructs (software companies' dataset)

Banking software firms								
Hypothesis	Dependent Variables (X)	Independent Variables (Y)	Effect	Direction	P value	R Squared	Correlation	Strength of direct relationship
H1	HE	EAPS	0.268	Positive	0.008	17.53%	0.42	Moderate
H2	HM	EAPS	0.481	Positive	0	33.64%	0.58	Moderate
H3	AIT	EAPS	0.399	Positive	0.001	27.73%	0.53	Moderate
H4	CDM	EAPS	0.341	Positive	0.005	19.29%	0.44	Moderate
H5	EAPS	CE	0.779	Positive	0	52.98%	0.73	Strong

HE = Human Emotions, CE = Customer Experience, AIT = AI Transparency, CDM = Co-Development Mindset, EAPS = Effective AI enabled products, HM = Human Minds

Table 8: Results of reliability analysis (FinTech companies' dataset)

Measure	Abbreviation	No of items	Cronbach's Alpha
Effective AI products and services	EAPS	6	0.900
Human emotions	HE	5	0.758
Human minds	HM	5	0.772
Co-development mindset	AIT	8	0.737
AI-transparency	CDM	8	0.914
Customer experience	CE	4	0.850

alpha for all measures were above the moderately reliable range.

The consolidated statistical results and the strength of the direct association between the dependent and independent variables of the five hypotheses applied to the FinTech companies' dataset are shown in Table 9.

Reliability analysis of focus group dataset

In total, 36 participants participated in the survey from 20 focus group companies. Table 10 shows the results of the reliability analysis in the study. The Cronbach's alpha values of all measures are in the highly reliable range except for the alpha value of 'HE'. After revisiting the survey questions prepared for the focus group companies, it was found that Q1 ('Understanding customer emotions helps to serve customer needs better') sounded more generic to the survey participants. Therefore, reliability was tested again after removing Q1. As a result of including only questions Q2 and Q3 under the 'HE' construct, the alpha value increased to 0.689.

ANOVA results and coefficients are shown in Tables 11 and 12.

Omitting Q1 from the focus group questionnaire did not result in significant

Table 9: Strength of relationship between constructs (FinTech companies' dataset)

FinTech Firms								
Hypothesis	**Dependent variables (X)**	**Independent variables (Y)**	**Effect**	**Direction**	**P value**	**R Squared**	**Correlation**	**Strength of direct relationship**
H1	HE	EAPS	0.583	Positive	0.001	32.26%	0.57	Moderate
H2	HM	EAPS	0.872	Positive	0	46.47%	0.68	Strong
H3	AIT	EAPS	0.455	Positive	0.004	25.34%	0.50	Moderate
H4	CDM	EAPS	0.715	Positive	0.003	27.22%	0.52	Moderate
H5	EAPS	CE	0.710	Positive	0	62.74%	0.79	Strong

HE = Human Emotions, CE = Customer Experience, AIT = AI Transparency, CDM = Co-Development Mindset, EAPS = Effective AI enabled products, HM = Human Minds

Table 10: Results of analysis (focus group's dataset)

Measure	Abbreviation	No of items	Cronbach's Alpha
Effective AI products and services	EAPS	7	0.832
Human emotions	HE	3	0.595
Human minds	HM	5	0.821
Co-development mindset	AIT	4	0.820
AI-transparency	CDM	4	0.652
Customer experience	CE	3	0.873

Table 11: ANOVA summary of HE on EAPS

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	8.345	1	8.345	42.117	.000[b]
	Residual	6.737	34	.198		

a. Dependent Variable: Effective_ AI Products_and_Services
b. Predictors: (Constant), Human_emotions

Table 12: Regression coefficients of HE

Coefficients[a]					
Model	Unstandardised coefficients		Standardised coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	1.837	.482		3.809	.001
Human_emotions	.613	.094	.744	6.490	.000

a. Dependent Variable: Effective_ AI_Products_and_Services

changes in the effectiveness of HCAI-enabled products and services with respect to the HE construct. Therefore, all the survey questions were included in the survey to test the hypothesis.

Analysis also revealed that the direct relationship between 'AI-transparency' and 'EAPS' was weak, as shown in Table 13. This weak relationship is likely due to the difference between the core capabilities of the focus group companies as compared to the core capabilities of the banking software companies and the FinTech companies.

DISCUSSION

Innovation labs/AI centre of excellence

Since AI technologies are niche, a demand exists for skilled resources. Unlike for traditional tools and technologies, AI technologies are quite complex, and it is challenging to identify AI-skilled resources. Furthermore, it is challenging for banking software companies and FinTech companies to retain existing AI-skilled resources and knowledge gained in AI-driven projects. It is recommended that banks establish AI innovation labs, AI innovation hubs, or AI centres of excellence (AI-CoE) in collaboration with FinTech companies or banking software companies that specialise in AI and banking technology.

It would be beneficial to banks, fintech companies and other stakeholders if a centralised platform for AI initiatives were established, incorporating best-in-class AI skills and sharing knowledge among all stakeholders in developing HCAI-related innovations. In addition to resourcing projects with an AI-skilled workforce, other domain-specific capabilities can be developed, eg the process of studying HE and understanding human minds as necessary for training HCAI models. Such a process requires knowledge from various other fields such as psychology, philosophy, anthropology and linguistics.[12] Furthermore, non-banking technology companies are investing heavily

Table 13: Strength of relationship between constructs (focus group's dataset)

Focus Group Firm								
Hypothesis	**Dependent variables (X)**	**Independent variables (Y)**	**Effect**	**Direction**	**P value**	**R Squared**	**Correlation**	**Strength of direct relationship**
H1	HE	EAPS	0.805	Positive	0	54%	0.74	Strong
H2	HM	EAPS	0.774	Positive	0	53.97%	0.73	Strong
H3	AIT	EAPS	0.449	Positive	0.017	15.64%	0.40	Weak
H4	CDM	EAPS	0.659	Positive	0	38.73%	0.62	Strong
H5	EAPS	CE	0.674	Positive	0	55.25%	0.74	Strong

HE = Human emotions, CE = Customer experience, AIT = AI transparency, CDM = Co-development mindset, EAPS = Effective AI enabled products, HM = Human minds in developing AI tools and techniques to provide better products and services for their consumers. According to recent market research, AI investment will reach US$191bn by 2025.[13]

The adoption of digital banking products and services is increasing consistently over time.[14] It is recommended that banks invest in and develop application programming interfaces (APIs) aligned to the Banking Industry Architecture Network (BIAN) which would allow banks to facilitate open and easy collaboration with FinTechs and regulatory technology (regtechs).[15,16] It is important for banks to gain business insights in order to improve customer experience and customer retention rates. This can be achieved by leveraging data captured through existing banking channels and BIAN-compliant APIs with the power of AI, with increased control over infrastructure, data and processes. Without an effective AI-CoE in place, the ongoing success of an AI implementation is at risk.

Co-development mindset

In recent years, banks have begun to realise the impact of innovative financial products offered by non-banking companies. Therefore, FinTech and other associated players should be viewed as potential collaborators rather than competitors.[17] Banks should implement a FinTech collaboration strategy which enables them to a reach a broader customer base.[18] According to the Global FinTech Database, most young adults in the European Union (EU) and other developed economies have engaged in FinTech payments-related transactions.[19]

To promote the banking sector to be robust and competitive, the Monetary Authority of Singapore (MAS) has awarded digital banking licences to non-banking IT enterprises.[20] Regulations have been enacted to allow new players to enter the mobile payments space. As a result, mobile manufacturing companies such as Apple and Samsung, search engine pioneers such as Google and FinTechs are gaining more impetus. These players are focusing on the digital banking space with a strong value proposition targeting superior customer experience.[21]

Recommendations are offered for critical areas to be further enhanced by banks, banking software companies and fintech companies to effectively leverage stakeholder capabilities and regulatory privileges. First, a nurturing, healthy and conducive environment has to be fostered with an open innovation mindset and culture. Evidence confirms that openness drives faster project implementation, enhanced technical performance and increased revenues.[22]

Secondly, the requirements for technical, business and functional aspects and goals should be discussed and agreed upon between key collaboration players, which will have a significant impact on new product development.[23] Furthermore, this approach will likely improve the revealed knowledge and the chances of consumer adoption.[24] In addition, this approach promotes trust between the product and the culture of close collaboration.

Thirdly, trust is another critical element to be fostered and embraced by all stakeholders. Initiatives must be taken to build trust among stakeholders before they start contributing collaboratively, which would motivate and push them forward to volunteer. With building trust, collaboration success rate will be much higher.[25]

Fourthly, by selectively revealing the know-how of the technology and business aspects to develop new features in collaboration with the focal companies through more secure channels (eg open API) to the external world, the effectiveness of HCAI can be further scaled to the external world, opening up new business opportunities. Robust monitoring of R&D projects research directions helps protect against undesirable knowledge leakages in areas beyond the partnership's scope, resulting in more productive grounds for R&D collaboration and an increase in the success ratio in developing new products.[26] Companies can exchange and share core resources, knowledge and capabilities in a robust business ecosystem by practising a co-development and collaboration strategy.[27]

Flexible governance and compliance

The financial services industry has seen a significant rise in AI usage in recent years. New product development, business operations, customer care and client acquisition are some business functions where AI may help.[28] The increasing importance of AI-driven decisions has heightened model governance and compliance demand. In the financial services industry, all AI models must adhere to risk management and regulatory compliance.[29] To govern AI-enabled products and services, it is necessary to have strong AI subject matter experts supervise and assist banks in understanding and handling related complexity, agility, performance, monitoring and testing of HCAI products. A strategic shift in governance tools is needed to replace conventional, sequential and manual methods with system-level approaches of AI-centric self-regulation, continuous monitoring and mitigation capabilities.

Agile methodology for HCAI product development

AI projects are more likely to experience setbacks and course adjustments during deployment because AI is new to the business world, especially in the banking sector. Agile methoology is better suited for AI implementation since it reduces redirection costs while delivering benefits faster. The key to agile development is allowing for scope and feature changes as the product develops. Agility helps product teams cope with dynamic changes using repeatable, predictable and reliable methods. Agile practices can help ML development by facilitating better communications, objectives comprehension and issues sharing. Agile methodology facilitates communication and collaboration between data scientists and operational specialists, which is critical for streamlining and automating ML operations (MLOps). The above-recommended AI-CoE /innovation hub/innovation lab should function in an agile framework to implement disruptive technologies such as AI.

'Fail fast and fail cheap'

Failures due to technical glitches in the banking industry significantly affect reputation at a high cost. Risk factors are increasing compared to the benefits gained from emerging technologies such as AI. Even if an innovation team functions in a cautious manner, it cannot escape failure. Early failure is good, as it is more manageable in terms of cost and impact severity and allows for a faster recovery process. The general advice for banks is 'fail fast and fail cheap'. The co-development mindset and collaboration strategy should allow for early failure and fast recovery. This mindset should be embedded in how banks collaborate with banking software companies, FinTech companies and focus group companies to develop HCAI products.

With the help of MLOps and AUTOML tools (no-code/low-code), a rapid AI experimentation approach can be adopted successfully by businesses of all sizes. Adopting such tools allows AI models to be continuously updated, learning from newly ingested data, providing ongoing live monitoring and predictions in less time. Rapid AI experimentation aids banks in scaling the usage of data for enhanced analytics and better decision making. To fail fast and cheaply, a proper mechanism and dedicated sandbox environment should be in place. MAS has made it clear in their presentation: 'It is something that the financial sector and the economy as a whole needs a lot more of – a spirit of experimentation.'[30]

AI model drift

Maintaining the quality of automated decisions is one of the biggest challenges in training AL models. A well-trained model can make ethical and unbiased decisions. Continuously integrating data from new sources to train models is unavoidable. Such data injection may change the linkages between input and output variables, which may degrade the quality of the model's decision-making approach, resulting in model drift. Due to this drift, models can become unstable and predictions can become erroneous. Model accuracy downgrades as predicted values deviate from actual values. Some techniques that help overcome model drift include retraining the model trained with old data and introducing a new model by referencing the old model as a baseline in an iterative process in the ML life cycle. Models need to be monitored periodically and retrained accordingly and constantly to overcome the risk of model drift.

Engaging with the right technology partners

Before engaging with any external technology partners, senior management should revisit and redefine their core objectives. First, management should have adequate knowledge and information about current AI developments and global trends in the banking domain. Secondly, management should clearly understand the primary business problems they plan to solve by adopting AI technologies, eg expanding and penetrating emerging markets. Thirdly, management should review partner/vendor profiles regarding their core capabilities, company size, market presence, completed projects and objectives aligned with the bank's objectives. Overall, co-development success is determined by a clear and shared direction between the bank and the collaboration company, a reasonable budget, and the ability to complete a pilot in order to decide whether to continue the partnership.

CONCLUSION

This research aims to uncover the significant obstacles and gaps in building HCAI-enabled products and services for a better customer experience in the banking industry, and to help banks to stay competitive through their digital transformation journey. The research survey was conducted among 39 software organisations, including the top core banking software companies, 31 FinTech companies specialised in developing

Table 14: Overall outcome of hypotheses testing (H1-H5)

Hypothesis	Decision
HI: The degree of processing human emotions positively influences the effectiveness of human-centered AI-enabled products and services.	Supported
H2: The degree of understanding the human mind positively influences the effectiveness of the human centered AI-enabled products and services.	Supported
H3: The degree of increase in AI transparency positively influences the effectiveness of human centered AI-enabled products and services.	Supported
H4: The co-development mindset between the IT vendor and the bank will positively influence the effectiveness of human-centered AI-enabled products and services.	Supported
H5: The effectiveness of human centered AI enabled products and services has a positive impact on the customer's experience.	Supported

Table 15: Strength of relationship between constructs (all datasets)

Banking software Companies								
Hypothesis	**Dependent variables X**	**Independent variables Y**	**Effect**	**Direction**	**P value**	**R Squared**	**Correlation**	**Strength of direct relationship**
H1	HE	EAPS	0.268	Positive	0.008	17.53%	0.42	Moderate
H2	UCM	EAPS	0.481	Positive	0	33.64%	0.58	Moderate
H3	AIT	EAPS	0.399	Positive	0.001	27.73%	0.53	Moderate
H4	CDM	EAPS	0.341	Positive	0.005	19.29%	0.44	Moderate
H5	EAPS	CE	0.779	Positive	0	52.98%	0.73	Strong

FinTech Companies								
Hypothesis	**Dependent variables X**	**Independent variables Y**	**Effect**	**Direction**	**P value**	**R Squared**	**Correlation**	**Strength of direct relationship**
H1	HE	EAPS	0.583	Positive	0.001	32.26%	0.57	Moderate
H2	UCM	EAPS	0.872	Positive	0	46.47%	0.68	Strong
H3	AIT	EAPS	0.455	Positive	0.004	25.34%	0.50	Moderate
H4	CDM	EAPS	0.715	Positive	0.003	27.22%	0.52	Moderate
H5	EAPS	CE	0.710	Positive	0	62.74%	0.79	Strong

Focus Group Companies								
Hypothesis	**Dependent variables X**	**Independent variables Y**	**Effect**	**Direction**	**P value**	**R Squared**	**Correlation**	**Strength of direct relationship**
H1	HE	EAPS	0.805	Positive	0	54%	0.74	Strong
H2	UCM	EAPS	0.774	Positive	0	53.97%	0.73	Strong
H3	AIT	EAPS	0.449	Positive	0.017	15.64%	0.40	Weak
H4	CDM	EAPS	0.659	Positive	0	38.73%	0.62	Strong
H5	EAPS	CE	0.674	Positive	0	55.25%	0.74	Strong

CE = Customer experience, HM = Human minds, AIT = AI transparency, CDM = Co-development mindset, EAPS = Effective AI enabled products, HE = Human emotions

AI-based banking products and solutions and 20 market research organisations offering focus group services across several verticals, including banks and software companies. Table 14 summarises the results of the hypotheses testing against all three datasets.

The strength of the direct relationship between the independent variables and the dependent variable of the three survey datasets is summarised in Table 15.

Overall, the research outcome supports the hypotheses, and the strength of the direct relationship between the theoretical model constructs are either ‘strong’ or ‘moderate’. There was one exception in the case of the focus group dataset where the direct relationship between AI-transparency and EAPS is weak; however, this was insignificant to the overall result. The research shows that capturing and processing HE for training AI models improves customer satisfaction and trustworthiness, and that a co-development mindset between IT vendors and banks will enhance the effectiveness of AI-enabled products.

References

1. Riedl, M. O. (2019), 'Human-centered artificial intelligence and machine learning', *Human Behavior and Emerging Technologies*, Vol. 1, No. 1, pp. 33–36.
2. Arul, O. K. (2022), 'Human-centered artificial intelligence: Creating a better customer experience in the banking sector', Doctoral Dissertation, Singapore Management University, available at https://ink.library.smu.edu.sg/etd_coll/401 (accessed 13th December, 2022).
3. Premack, D. and Woodruff, G. (1978), 'Does the chimpanzee have a theory of mind?', *Behavioral and Brain Sciences*, Vol. 1, No. 4, pp. 515–526.
4. Philbeck, T., Davis, N. and Larsen, A. M. E. (2018), 'Values, ethics and innovation: Rethinking technological development in the Fourth Industrial Revolution', World Economic Forum, available at https://www3.weforum.org/docs/WEF_WP_Values_Ethics_Innovation_2018.pdf (accessed 13th December, 2022).
5. Joshi, S., Majumdar, A. and McCoy, A. (2014), 'Enhancing customer experience using business intelligence tools with specific emphasis on the Indian DTH industry' *Procedia Economics and Finance*, Vol. 11, pp. 289–305.
6. Hakim, C. (2000), *Research Design: Successful Designs for Social and Economic Research*, Psychology Press, London.
7. Salant, P., Dillman, I. and Don, A. (1994), *How to Conduct Your Own Survey*, Wiley, Hoboken, NJ.
8. Hon, W. K., Millard, W. K. and Millard, C. (2016), 'Use by banks of cloud computing: An empirical study', Research Paper No. 245/2016, Queen Mary School of Law Legal, London.
9. Temenos (2019), 'Digital Banking', available at https://193.108.160.149/handle/repo/43353 (accessed 13th December, 2022).
10. Hinton, D., So, V., Pollack, M. H., Pitman, R. K. and Orr, S. P. (2004), 'The psychophysiology of orthostatic panic in Cambodian refugees attending a psychiatric clinic' *Journal of Psychopathology and Behavioral Assessment*, Vol. 26, No. 1, pp. 1–13.
11. Cronbach, L. J. and Shapiro, K. (1982), *Designing Evaluations of Educational and Social Programs*, Jossey-Bass, Hoboken, NJ.
12. Malle, B. F. (2005), 'Folk Theory of Mind: Conceptual Foundations of Human Social Cognition', in Hassin, R., Uleman, J. S. and Bargh, J. A. (eds), *The New Unconscious*, Oxford University Press, Oxford.
13. Tech Advisor Staff (2019), 'How tech giants are investing in artificial intelligence', Tech Advisor, available at https://www.techadvisor.com/feature/small-business/tech-giants-investing-in-artificial-intelligence-3788534/ (accessed 13th December, 2022).
14. Business of Apps (2022), 'Apple Statistics (2023)', available at https://www.businessofapps.com/data/apple-statistics/ (accessed 13th December, 2022).
15. Benmoussa, M. (2019), 'API "Application Programming Interface" Banking: A promising future for financial institutions (International experience)', ASJP, available at https://www.asjp.cerist.dz/en/downArticle/360/18/2/104940 (accessed 13th December, 2022).
16. Abediniyan, A., Azar, F. M. and Nazemi, E. (2021), 'Designing a model to use Omnichannel in banking industry based on BIAN framework', 2021 5th National Conference on Advances in Enterprise Architecture (NCAEA), pp. 1–10.
17. Capgemini/BNP Paribas (2017), '2017 World Payments Report', available at https://www.capgemini.com/fr-fr/wp-content/uploads/sites/2/2017/10/world-payments-report-2017_year-end_final_web-002.pdf (accessed 13th December, 2022).
18. Edgar, Dunn & Company (2017), 'Payments Report', available at www.edgardunn.com (accessed 13th December, 2022).
19. Beck, T., Cecchetti, S. G., Grothe, M., Kemp, M., Pelizzon, L. and Sánchez Serrano, A. (2022), 'Will video kill the radio star? Digitalisation and the future of banking. Digitalisation and the Future of Banking (January 1, 2022)', ESRB: Advisory Scientific Committee Reports, p. 12.
20. MAS (2019), 'MAS to Issue up to Five Digital Bank Licences', available at https://www.mas.gov.sg/news/media-releases/2019/mas-to-issue-up-to-five-digital-bank-licences (accessed 13th December, 2022).
21. Omarini, A. E. (2018), 'FinTech and the future of the payment landscape: The mobile wallet ecosystem – A challenge for retail banks?', *International Journal of Financial Research*, Vol. 9, No. 4, pp. 97–116.
22. Du, J., Leten, B. and Vanhaverbeke, W. (2014), 'Managing open innovation projects with science-based and market-based partners', *Research Policy*, Vol. 43, No. 5, pp. 828–840.
23. Petersen, K. J., Handfield, R. B and Ragatz, G. L. (2005), 'Supplier integration into new product development: Coordinating product, process and supply chain design', *Journal of Operations Management*, Vol. 23, Nos. 3–4, pp. 371–388.
24. Alexy, O., George, G. and Salter, A. J. (2013), 'Cui Bono? The selective revealing of knowledge and its implications for innovative activity', *Academy of Management Review*, Vol. 38, No. 2, pp. 270–291.
25. Nidumolu, R., Ellison, J., Whalen, J. and Billman, E. (2014), 'The collaboration imperative', *Harvard Business Review*, Vol. 92, No. 4, pp. 76–84.
26. Business of Apps, ref. 14 above.
27. Tafti, A., Sachdev, V., Mithas, S. and Mallik, L. (2015), 'Alliances, R&D and profitability of software firms', 2015 International Conference on Information Systems: Exploring the Information Frontier, ICIS 2015, pp. 1–17.
28. Kurshan, E., Shen, H. and Chen, J. (2020), 'Towards self-regulating AI: Challenges and opportunities of AI model governance in financial services',

Proceedings of the First ACM International Conference on AI in Finance, pp. 1–8.
29. Scherer, M. U. (2015), 'Regulating artificial intelligence systems: Risks, challenges, competencies, and strategies', *Harvard Journal of Law & Technology*, Vol. 29, No. 2, p. 353.
30. Finacle Connect (2018), 'Artificial Intelligence Powered Banking', Vol, No. 5.